# The Gender Gap in College Major: Revisiting the Role of Pre-College Factors

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**Abstract**

This paper considers the importance of pre-college academic factors in accounting for gender gaps in college major curriculum. Large gaps in major content exist; men are more likely to study math-, science-, and business-intensive fields, while women are more likely to study humanities-, social science-, and education-intensive fields. Women are also more likely to switch out of a science or engineering major conditional on starting one. Previous research has found that gender differences in college preparation, typically measured by SAT scores, can account for only a small portion of these differences. Using a broader array of pre-college test scores (the ASVAB), I show that differences in college preparation can actually account for a large portion of most gender gaps in college major content, including two-thirds of the gap in science, half of the gap in humanities, and almost half of the gap in engineering. By contrast, business and education retain large gender gaps even when controlling for abilities. A smaller portion

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(at most 22%) of women's higher likelihood of switching out of a science or engineering major is explained by the ASVAB scores, suggesting that most ability sorting into majors occurs at the beginning of college. I show that gender gaps in test scores, particularly in science and mechanical fields, exist by the mid-teenage years and typically grow with age. While there are gender differences in middle and high school course-taking, they do not explain the increasing gender gaps in test scores.

# 1 Introduction

Gender differences in college major choice are well known and have been studied by researchers across many disciplines. Men are more likely to study science, engineering, and business, while women are more likely to study humanities, education, and some social sciences like psychology. Given that male-dominated majors are typically associated with higher-earning occupations, the difference in major choice is an important component of the gender wage gap (Brown and Corcoran 1997).

In this paper, I study the relationship between pre-college academic factors, as measured by a battery of test scores, and college major content.[1] Previous research has generally found that differences in college preparation between males and females can only account for a small portion of the gender gap in major choice. I improve on this prior work by using a richer set of ability measures in a wide variety of subjects, including math, verbal, science, and mechanical abilities. I also characterize college majors as bundles of course content, which allows for more detailed analysis than a traditional categorization of majors. Using these measures, I find that pre-college factors can account for a large portion of gender gaps in major content, including two-thirds of the gap in science and about half of the gaps in the humanities and engineering.

I then study a related issue: conditional on starting a science-related major, women are more likely to switch out of science. I ask if this, too, can be explained by pre-

[1] By pre-college factors, I mean the sum of all the forces that have shaped one up until the time the test score is measured. This includes innate ability but also parental, school, peer, and environmental influences. I also sometimes use the word "ability" to mean the accumulation of these factors. Where I mean innate or biological ability, I say so explicitly.

college factors. Using data that allow me to identify college major switches, I find that a smaller portion – at most 22% – of women's higher likelihood of switching out of science majors is due to preparation differences. I use these results to frame a discussion of the mechanisms potentially responsible for the major-switching behavior of men and women.

Finally, I investigate the timing and origins of the gender gaps in test scores. I show that gender gaps in test scores, particularly in science and mechanical subjects (which are highly predictive of going into STEM majors), are present by age 15, the earliest age I can observe. The gaps then grow with age, so that boys widen their advantage in these fields as they get older. One possible reason for this pattern is gender differences in course-taking. I show that, while boys do take more courses in shop and some science fields, this cannot explain much or any of the gender gaps in test scores.

Gender gaps in college major are hardly a new topic for research. Among many others, Turner and Bowen (1999), Daymont and Andrisani (1984), Arcidiacono (2004), and Zafar (2013) have studied this issue, and the existence of large gender gaps, particularly in science, engineering, and humanities, is not controversial. Dickson (2010) has shown that the gender gaps in major choice are much larger than the racial gaps.

What is somewhat remarkable about the gender gaps in major choice is their persistence over time, even in the face of dramatic changes in the gender makeup of college students and graduates. As Goldin, Katz and Kuziemko (2006) report, female college enrollments have increased relative to those of males steadily over the last 70 years. In 1947, there were 2.3 undergraduate males per undergraduate female; by 1960, the ratio was down 1.55, and by 2003, females outnumbered males by a ratio of 1.3 to 1. They propose several explanations for this reversal, one of which is girls' improved preparation for college relative to boys, including taking more math and science courses. Despite this, the share of undergraduate degrees earned by women in some science-related fields, including engineering and computer science, has stayed largely flat or even declined (see Figure 1). Turner and Bowen (1999) note that the gender gaps in education and business majors have narrowed some over time, but remain large.

A number of explanations for these gender gaps in college major have been explored by researchers using both qualitative and quantitative methods. Turner and Bowen (1999) use SAT math and verbal scores as measures of college preparation and find that this can account for only a minority of the gender gap in majors; they point to other factors, including differences in preferences and labor market expectations, as the main determinants of the gaps.[2] Similarly, Dickson (2010) finds that aggregate SAT and ACT scores explain little of the gender gaps in majors or in differential switching out of engineering majors by gender. Paglin and Rufolo (1990), looking primarily at occupational choices and earnings, find that pre-college quantitative abilities (such as the SAT math score) explain some of the male-female major gap and earnings gap.

Ware, Steckler and Leserman (1985) look at the determinants of majoring in science and find that high SAT math scores and highly educated parents are positive predictors. As in the other papers, this does not seem to account for much of the gender gap. Taking a more structural approach, Arcidiacono (2004) concludes that, "Virtually all ability sorting [across majors] is because of preferences for particular majors in college and the workplace." Similarly, Zafar (2013) studies the major choices of a set of Northwestern University students and concludes that, "The gender gap is mainly due to gender differences in preferences and tastes" and not discrimination or differences in academic preparation. The consensus in this literature seems to be that pre-college academic factors, as typically measured by SAT or ACT scores, are not the driving factor in the gender major gap.

Some papers have investigated other possible mechanisms besides academic preparation. Carrell, Page and West (2010) take advantage of the random assignment of students to professors at the U.S. Air Force Academy and find that having a female professor in math and science courses has a large effect on the performance of female students and on their likelihood to major in a STEM (science, technology, engineering, and mathematics) field. In fact, according to their results, the gender gap in STEM majors is eliminated when students are assigned to a female professor in their mandatory math and science courses. One wonders about the generlizability of results from the Air Force to all students, but the finding is still striking.[3]

[2] According to College Board data, men currently score about 30 points higher than women on the SAT math component, while women score higher on the writing section. Verbal scores are similar for men and women.

[3] Looking at three elite colleges, Canes and Rosen (1995) find no evidence that increasing the share of women on the faculty of a department increases the share of female majors in that department. However, they do not have data on whether students actually took courses with each professor. Ware and Lee (1988) find that the influence of high school teachers and counselors is an important

Other common explanations for the gender gap in majors appeal to differences in preferences and expectations about majors and the labor market (e.g., Arcidiacono (2004), Daymont and Andrisani (1984)). In these explanations, females may steer away from STEM majors because of a preference for "helping" fields or a more cooperative workplace. Brown and Corcoran (1997) propose that the return to majors differ by field, and therefore differing choices of men and women may be a response to those differential returns.

Finally, a recent literature examines the phenomenon of switching out of a STEM major after starting in one. Stinebrickner and Stinebrickner (2013a, 2013b), using longitudinal data from students at Berea College, find that students enter college over-optimistic about their own ability in math and science and about their chances of completing a degree in those fields. As students learn about their true level of ability, the less able students switch to less challenging majors. They suggest that the best method of increasing the number of STEM majors is to undertake policies that improve pre-college preparation in those subjects. Arcidiacono (2004) also looks at major switches and finds that while switching out of science fields is common, switching into science fields is rare.[4]

This paper studies college major choice and major-switching behavior, revisiting the importance of pre-college academic factors. Instead of relying on SAT and ACT scores, I make use of the Armed Services Vocational Aptitude Battery (ASVAB) tests in the National Longitudinal Survey of Youth data sets. These tests provide me with a detailed pre-college ability vector for each student, including measures of math, reading, science, and mechanical abilities. I show that having this wide array of ability measures dramatically improves our ability to understand college major choice. These data also allow me to look at major-switching behavior, because I observe a major observation for each college student in each year. Using the ASVAB scores, I can ask if these detailed ability measures predict switching behavior and if they account for any differential switching by gender.

This is the first paper that I am aware of to use the ASVAB scores to study college major choice and major switching behavior in detail. Because my results differ

determinant of majoring in science for females.

[4]Arcidiacono's (2004) model is based on Altonji (1993), who studies the choice of major as a function of ability, preferences, returns, and knowledge accumulation.

substantially from previous work using SAT or ACT scores, the use of these data is a major contribution.

I have two key findings, both of which are made possible by the use of the ASVAB scores. First, pre-college academic factors account for a large portion of many gender gaps in college major content, including 67% of the gap in science, 45% of the gap in engineering, half of the gap in humanities, and 26% of the gap in mathematics. By contrast, some fields, particularly business- and education-heavy majors, retain large gender gaps even when controlling for test scores.

Second, a smaller portion (at most 22%) of women's higher likelihood of switching out of science majors (conditional on starting them) is due to academic preparation. Women enter college with lower science and mechanical test scores, and higher verbal test scores, and these differences account for a portion of the propensity to switch out of science majors. However, the vast majority of the gender gap in switching behavior remains and is not due to pre-college abilities. This implies that while students sort into majors on ability, most of this sorting occurs at the beginning of college. Switching during college is mostly driven by non-ability factors.

Finally, I ask at what ages the large test score gaps between men and women appear. Taking advantage of the age structure of the NLSY, I observe gender test score gaps among test takers of different ages. In general, test score gaps – particularly in science and mechanical subjects – are present in the mid-teenage years and then widen substantially as age increases.

The remainder of the paper is organized as follows. In section 2, I display some summary data on gender gaps in college majors and discuss some popular explanations for these gaps. Section 3 discusses the data, Section 4 presents the key results, and Section 5 concludes with a discussion of the results and their importance.

# 2 Gender Gaps in College Majors

In section 4, I will use the NLSY data to document the gender gaps in college major content in my sample. Here, I provide some summary measures using data from the National Science Foundation's *Women, Minorities, and Persons with Disabilities in Science and Engineering* report (NSF 2014). Figures 1 (BA degrees) and 2 (PhDs) summarize these data from 1991 to 2010. Women's shares of bachelor's degrees awarded vary widely across fields, from 77% in psychology to 18% in engineering in 2010. It is generally highest in social sciences and biosciences and lowest in some "STEM" fields, including physical sciences, computer science, and engineering. Some of these shares have changed considerably over time, with women growing as a share of psychology, bioscience, social science, and physical science BAs. However, women have made little progress in math or engineering and have seen a significant decline in their share of computer science degrees.

The PhD data in Figure 2 tell a similar story, although women have generally made more progress over the last 20 years in PhDs than in BAs, particularly for fields like engineering and computer science. Still, in 2010, only 23% of engineering PhDs and 22% of computer science PhDs were awarded to women.

The gender gaps in college major are manifest in occupational outcomes as well.[5] According to the American Community Survey, women made up 13% of engineers, 27% of computer workers, and 61% of social scientists in 2011, figures similar to the degree statistics.

## 2.1 Potential Explanations

Many explanations have been proposed for the underrepresentation of women in STEM majors and occupations, both in academic work and in the popular press. Perhaps a natural first hypothesis is that men and women bring different abilities to college and to the labor market, and this results in different major and occupational outcomes. These types of hypotheses can take two forms. One says that there is some biological or innate ability difference between men and women, or at least a difference in the variance of those abilities. Former Harvard University President Lawrence Summers famously suggested that differences in "intrinsic aptitude", particularly in the variance of math and science ability, might explain the lack of female reprsentation among scientists and engineers (Summers 2005).

However, an ability-based explanation need not appeal to biology or innate ability. "Ability" differences that exist by the time of college or labor market entry (as mea-

[5]For a detailed analysis of gender gaps in occupational outcomes, see Speer (2015).

sured by test scores, for example) could be produced by many factors, including prior academic choices, parental investments, and discrimination. If, for example, young girls are discouraged from studying math and science, test score gaps could exist by age 18 that have nothing to do with biology. Thus, ability-based explanations are not inconsistent with other theories.

As discussed above, the consensus in the economics literature has been that pre-college academic factors can explain only a minority of the gender gap in college major (e.g., Arcidiacono (2004), Turner and Bowen (1999)). However, several other theories have gained traction both in the academic literature and the popular press.

Some theories of women's underrepresentation in STEM cite institutional biases, such as pay differences and the lack of encouragement for women from high school and college advisors. In one study of science faculty, student resumés with identical qualifications were evaluated differently by faculty, with females being seen as less qualified (Moss-Racusin et al. (2012)). These institutional biases may also produce "internal" biases, in which women believe they are not smart or qualified enough to pursue careers in math and science.

Even if ability is not different for boys and girls, self-assessed ability and self-condidence may be different. Bharadwaj, de Giorgi, Hansen and Neilson (2012) show evidence (in developing countries) that girls are more likely than boys to state that math is difficult and that girls report lower self-assessed ability than boys. It may be, then, that girls internalize societal expectations and discrimination, resulting in lower self-confidence even when their ability is adequate.[6] A number of papers also stress different levels of competitiveness between men and women (see Niederle and Vesterlund (2011) for a survey). Laboratory experiments often show women to be less competitive than men, and this may explain why they shy away from more prestigious or difficult academic and career tracks, such as STEM fields, even when they are able (Buser, Niederle and Oosterbeek 2014).

The "culture" of STEM fields is also sometimes cited as an impediment to female participation.[7] STEM fields, the hypothesis might go, value assertiveness and individual ambition, while women are socialized to value communal achievement and

[6] Zafar (2013), however, finds evidence against this hypothesis among students at Northwestern University.

[7] For a detailed discussion of these issues in the popular press, see Pollack (2013).

deferrence. Math and science fields may also be seen as nerdy and not optimal for attracting husbands. A related explanation says that the lack of female role models in STEM fields, both in real life and in popular fiction, contributes to females' unwillingness to enter these fields. Furthermore, women who do enter STEM fields may feel isolated from other women and alienated in the male-dominant culture. In computer-related fields in particular, some commentators note the "brogrammer" culture, where sexist jokes and hostility to women are tolerated and encouraged.

Finally, a common refrain, which is consistent with multiple other theories, is that girls are simply raised to be interested in subjects other than math and science. While boys are given chemistry sets and robot kits, girls are given dolls. This may be the result of the type of discrimination and biases discussed above, and it may be a *cause* of ability differences that appear in males and females by the teenage years.

# 3 Data

The NLSY79 and NLSY97 are nationally representative panel surveys whose respondents were aged 14 to 22 and 12 to 16, respectively, at the start of the surveys and have been followed through the present. There are two key factors that make the NLSY ideal for this project. First is the inclusion of the Armed Services Vocational Aptitude Battery (ASVAB) tests, which were taken by NLSY97 respondents in 1999 and NLSY79 respondents in 1981. The ASVAB covers ten subjects: general science, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, coding speed, auto and shop information, mathematics knowledge, mechanical comprehension, and electronics information. This allows me to observe a worker's pre-college ability level in a variety of subjects with relevance to the choice of college major.

I restrict most of my analysis to respondents who took the ASVAB before turning 19, which includes all of the NLSY97 and about one-quarter of the NLSY79. For these respondents, ASVAB scores can be interpreted as pre-college accumulated abilities. For respondents who took the ASVAB after turning 19, there is a concern of reverse causality – college major influencing test scores, rather than the other way around. In section 4.3, I show that birth year does indeed have important effects on test scores that affect our understanding of the gender gaps.

The AFQT score, a linear combination of the ASVAB's math and verbal components, is commonly used by researchers to study a variety of outcomes, from college attendance to occupational outcomes to wages (see Cawley, Heckman and Vytlacil (2001) and Neal and Johnson (1996) for two examples). However, the broader set of test scores has been used much less frequently to study these types of outcomes. Speer (2015) shows that the ASVAB scores have important predictive power for the occupational outcomes of workers and can account for a significant portion of occupational gender gaps. For example, while the AFQT score explains almost none of the gender gap in science and engineering occupations, the broader set of ASVAB scores can account for about 70% of this gap.

In this paper, I use the same approach to study gender differences in college major. While AFQT scores differ very little across gender, men and women score well on different types of tests within the ASVAB. Figure 3 shows AFQT scores for males and females; it is clear that there is little difference. Women score slightly higher than men, while men have a higher variance of scores. As I show in the results, these differences explain only a very small portion of college major gaps.

Figure 4 shows scores in six of the ASVAB components separately by gender.[8] Here, we see that there are major differences for men and women. Men and women score similarly on mathematics knowledge and word knowledge, but women score higher on paragraph comprehension. Meanwhile, men dominate on the three science- and mechanical-themed tests: general science, automotive information, and mechanical comprehension. This is particularly true at the top of the distribution. For example, about 15% of men score above the 99th percentile of women on the automotive test.[9][10]

The second advantage of the NSLY is information on college major. Respondents are asked about their field of study each year, which allows me to look at both the final realized major and major changes along the way. I consider two majors: the "first" major and the "final" major. The first major is the first major reported by the respondent after entering college. The final major is the major reported by a respondent

[8] All scores are normalized by the quarter-year of birth.

[9] The gaps in the the science, mechanical, and automotive tests play a key role in accounting for gender gaps in occupation (Speer 2015).

[10] It should be noted that the set of ASVAB tests is skewed toward traditionally male subjects, due to its origins in the military. Ideally, one would have a complete set of ability measures, which would also include more traditionally female fields.

after he has just finished college (but before entering graduate school). While there may be more changes to major during a student's college career, these categories capture the idea of a student's first intention and his or her realized outcome.[11]

The NLSY79 questions on college major offer several hundred choices; over 300 different majors are reported by respondents. On the other hand, the NLSY97 questions offer less than 40 different options. Rather than analyzing each major separately, I need a convenient method of analyzing these majors and their relationships to other majors. To do this, I require two things: (a) a way to categorize the majors consistently across the two surveys, and (b) a way to characterize the majors by content.

The solution used by most researchers is to put the majors into categories: sciences, social sciences, humanities, etc. This has some intuitive appeal and maps nicely into common conceptions of major categories. However, it also has serious limitations for studying gender differences in college major and masks important differences within major group. For example, according to the American Community Survey, within the category of physical sciences, women represent about half of recent chemistry graduates but only about 28% of recent physics graduates.

While I will use this type of major categorization in some of my analysis, it is not my primary way of characterizing majors. Instead, I opt to characterize majors in a way that can be applied consistently across the two surveys nad provides rich detail on the makeup of majors. I first map the major categories in both surveys into a set of 51 categories used by the Department of Education. I then link these majors to information about their typical course content, calculated by the Department of Education from the Baccalaureate and Beyond data set.[12]

Table 1 shows a sampling of the college major data. Each major is a bundle of characteristics. For each of 51 majors, I have the average SAT math and verbal scores and the average number of credits in a variety of categories that are taken by students with that major.[13] For example, a mathematics major takes an average of 30

[11]About 90% of those who finish college and report a major report 1 to 3 majors, so it is not common for respondents to report many major changes, partly because "No major" is a possible response. Looking at the first and final majors reported throws away little information.

[12]For more detail on the major categories, see Altonji, Kahn and Speer (2015).

[13]The averages by major are computed by the Department of Education from the Baccalaureate and Beyond data set, which is restricted-use. Therefore, some of the SAT values are not given for smaller majors.

math credits, 13.7 science and engineering credits, and 14.3 social science credits. The average number of math credits is only 4.9, and 30 is the maximum value of all majors. Similarly, the science and engineering credits are highest for science and engineering majors. The patterns in the major credit data are therefore consistent with what one might expect to find.[14]

The advantages in using this way of characterizing majors are twofold. First, it emphasizes that when a student chooses a major, she is choosing a bundle of characteristics, and that even majors in the same broad grouping may differ in important ways. Second, it allows a richer analysis of major content gaps by allowing majors to differ along multiple dimensions. There are some questions that this characterization cannot answer (e.g., what accounts for the gender gap specifically among engineering majors?), and so I will also rely on more traditional measures, but I believe that my primary measure provides significant advantages. In practice, results using a more traditional categorization of majors are similar to mine.

For obvious reasons, I restrict my analysis to those who completed a college degree. I also delete the few observations without valid ASVAB scores. To ensure that the test scores are measured before typical college ages, I restrict to respondents born in 1963 or later in the NLSY79.[15] Table 2 contains summary statistics for my sample.

# 4 Results

I now present three sets of results. First, I ask how much of the gender gaps in the college major content can be accounted for by the ASVAB scores. I also perform a similar analysis for race, although this is not the primary focus of this paper. Second, I look at the propensity to switch out of math- and science-heavy majors. Third, I analyze the gender gaps in test scores by age/birth year to learn about when these gaps first appear and how they change with age.

[14]The data I use from the Department of Education has 51 major categories, but a few of these are empty in the NLSY. Therefore, this table only contains 42 major categories. Furthermore, some of the majors have small sample sizes in the Baccalaureate and Beyond data, so their average SAT scores are not publicly available.

[15]The tests were taken in 1981 in the NLSY79 and 1999 in the NLSY97, meaning that all of the NLSY97 repsondents are included in my analysis.

## 4.1 Accounting for the Gender Gap in College Major Content

I first quantify the race and gender gaps in college major course content in the NLSY data sets. In Table 3, I regress each major characteristic on race and gender with no ability measures included. The major characteristics I use are math, humanities, business, social science, education, and science and engineering courses (all measured in credit hours), average SAT math score in the major, and an indicator for being an engineering major.[16]

The gender gaps in college major content are substantial. For example, men's majors feature 1.7 more math credits, 3.0 more business credits, and 4.9 more science and engineering credits than those of women; men are also 8.7 percentage points more likely to be engineering majors, holding race and ethnicity constant.[17] Women's majors feature significantly more humanities, education, and social science credits, although only the education gap is large (4.7 credits). Overall, men are in majors whose students average 20 points higher on the SAT math test. These results are in line with the NSF data discussed earlier and shown in Figures 1 and 2.[18]

The race and ethnicity gaps are generally smaller than the gender gaps, but are still sometimes significant. In particular, both Hispanics and non-Hispanic blacks are more likely to be found in social sciences, while blacks are found in less science-related majors.[19] Both blacks and Hispanics are found in majors with lower SAT math scores. As I show below, the racial and ethnic gaps are somewhat less interesting than the gender gaps, because they can generally be explained by inclusion of a single test score, the AFQT.

Before I ask how much of these gaps can be accounted for by test scors, I need to establish that the ASVAB scores are predictive of college major content. In Table 4, I

[16] This final column is a probit regression, where I report the marginal effects rather than the estimated coefficients. The other regressions are all estimated using Ordinary Least Squares.

[17] In the raw data, 10.8% of men and 1.9% of women are engineering majors.

[18] To shed light on changing gender gaps over time, Appendix Tables 1 and 2 replicate Table 3 for the NLSY79 and NLSY97 separately. Here I use the whole of both surveys, not restricting to those who took the ASVAB before age 19, so I can get a full comparison of the two time periods. The most interesting findings here are that the science and engineering gap has been cut by about a third in the 20 years between surveys, and the gap in the probability of majoring in engineering has been cut by almost 25%; however, both of these gaps are still large in the NLSY97 data. The education gap has narrowed a bit, while the business gap has remained steady over this time period.

[19] The omitted category is non-black non-Hispanics.

regress the same college major characteristics on the ten ASVAB test scores, omitting race and gender. The relationships are generally as one would expect. Math courses are positively predicted by math and artihmetic test scores and negatively predicted by the verbal scores (word knowledge and paragraph comprehension). On the other hand, humanities courses are strongly positively predicted by the verbal tests and negatively predicted by the math tests.

Science and engineering courses are, perhaps unsurprisingly, positively predicted by the math ASVAB score. However, there are also very large positive effects of the science, mechanical, and electronics tests, as well as a large negative effect of the word knowledge test. Science and engineering-heavy majors attract students high in both math and science/mechanical ability. Given that men score much higher on the science and mechanical tests and women higher on the verbal tests, one immediately wonders whether this may account for the gender gap in science and engineering course content.

One important lesson from Table 4 is that majors are influenced not only by whether a student has high ability in that field, but also by what other abilities he or she brings into college. A student scoring highly in math, for example, is more likely to enter math-intensive majors, but if he is also proficient in reading and writing subjects, this can offset the effect of high math scores. Similarly, a student may shy away from science or engineering because he is less proficient in those subjects, but even a student good at science may shy away if he is also good in other subjects like reading and writing.

The final step is to include race, gender, and ASVAB scores in the same regressions and observe how the race and gender gaps change with the inclusion of the test scores. I summarize the results in Tables 5 (for gender) and 6 (for race). In Table 5, the first column shows the coefficient on "male" in a regression that only includes race and gender (as in Table 3). Column 2 shows the coefficient on "male" when the AFQT score is included. Column 3 shows the coefficient on "male" when all ASVAB scores (and not AFQT) are included.[20]

Several of the results for gender are dramatic. While including the AFQT score does almost nothing to account for gender gaps, the inclusion of the full range of ASVAB scores does significantly better.[21] Half of the humanities gap is explained when I

[20]The full results underlying Tables 5 and 6 are available upon request.

[21]Including parental education at the AFQT stage also does nothing to explain any of the gender

include the ASVAB scores, as are 67% of the science and engineering gap and 44% of the probability of majoring in engineering. In addition, the ASVAB scores account for 26% of the math course gap and 87% of the social sciences gap. 22% of the gap in the average SAT math score of the major is explained by the ASVAB scores.[22]

The two key exceptions are business and education, which maintain a large gender gap even when abilities are accounted for. The large male advantage in business courses is actually larger once we control for the ASVAB scores. This result is mostly due to the negative effect of the science and mechanical test scores on business courses, which works against explaining the male business advantage. The other exception is education, where the female dominance remains large when the test scores are included.

Appendix Tables 3 and 4 perform the analysis separately on the NLSY79 and NLSY97. Recall that most of the NLSY79 is not usable for this exercise, because the ASVAB tests are taken prior to college age for only the oldest survey respondents, so the NLSY79 sample here is small. Still, these tables provide an interesting comparison. Generally speaking, a smaller share of the gender gaps (particularly in STEM) is explained by pre-college factors in the later survey. Using the NLSY79 alone (Appendix Table 3) has another advantage: I can include measures of "noncognitve skill", the Rosenberg Self-Esteem Score and the Rotter Locus of Control score.[23] As the table shows, noncognitive measures do nothing to explain any of the gender gap in major content. All of the work here is being done by the ASVAB scores.

Table 6 repeats the analysis of Table 5 for the "black" coefficient in the major regressions. Here, the inclusion of all ASVAB scores is not necessary to account for most of the gaps in major content; the inclusion of the AFQT alone usually accounts for all of the gaps. In fact, in many cases, once we control for the full set of ASVAB scores, the gaps are in the opposite direction from the raw gaps. For instance, blacks are found in lower-science-content majors, but once we control for test scores, they actually take more science. This result – that controlling for a single test score can

gaps in major.

[22]Most of the work in explaining gender gaps is being done by the automotive, science, mechanical, and electronics tests, and including all of these is necessary; no single test score explains a large portion of the gender gaps on its own. When entered individually, however, the mechanical knowledge score is the one that explains the largest percentage of the science and engineering gender gap.

[23]See Heckman, Stixrud and Urzua (2006) for more detail on these measures and their interpretations.

account for most or all of the racial gaps – is consistent with the results of Neal and Johnson (1996) for wages and Speer (2015) for occupations.[24]

All of the analysis here holds when using a more traditional categorization of majors rather than my vectors of major course content. For instance, in probit regressions on STEM majors, about 60% of the gender gap is accounted for by ASVAB scores, while a slightly negative percentage of the business gap is explained. Thus, my method of characterizing majors allows for a more detailed analysis, and the results are consistent with those using other characterizations.[25]

### 4.1.1 Interpretation of ASVAB Results

It is important to point out once more that finding a strong role for pre-college test scores in the determination of college major, and in gender gaps in college major, is *not* clear evidence that discrimination and culture are insignificant factors. These results could be consistent with women being discouraged to pursue science or engineering because of these factors, but the results suggest that such discrimination may begin relatively early in life and not just in college, leading to ability gaps upon college entry.[26] If there is a cultural component of some fields that discourages women (and minorities) from entering, it may not begin in college or in the workplace, but earlier. In section 4.3 below, I investigate this further by looking at test score gender gaps at different ages to determine when the gaps open up. This will help us to understand when the key factors are doing their work.

[24] For all results in Tables 4-6, adding interactions between test scores leaves the results unchanged. In other words, adding interactions does not explain the gender gaps to any greater degree than the simple specification I use.

[25] Because I am restricting to those who finish their degrees, one might be concerned about some sample selection bias. I have also performed all of this analysis on the full sample of those who start college but do not finish; in this sample, the same broad patterns hold, but the ASVAB scores generally explain a smaller portion of the gender gaps in major content than they do in the restricted sample. This may suggest that there is stronger ability sorting into majors among those who actually finish a degree.

[26] Alternatively, discrimination may be anticipated ahead of time by girls or their parents, who do then not invest in science abilities.

## 4.2 Switching Out of Math and Science

Next, I turn my attention to the phenomenon of starting in a STEM major and then switching to a less quantitatively demanding major. Using longitudinal data at a single college, Stinebrickner and Stinebrickner (2013a, 2013b) analyze the major-choosing process of students initially interested in a science major. They find that students initially overestimate their ability to perform well in science, and once they adjust their beliefs about their own ability, many students switch to less demanding majors. In this story, then, the substantial flows out of science majors from the beginning of college to graduation are due to initial mistakes in student beliefs. In other words, if one has measures of students' true academic abilities in science-related subjects, one ought to be able to predict who will switch out of science majors and who will remain.[27]

An alternative possibility is that the culture of science, engineering, and math fields causes otherwise able students to switch to other fields.[28] In this story, gender often plays a key role. For instance, a popular hypothesis holds that the culture of science and engineering may be chauvinistic, competitive, or not family-friendly, leading women interested in science to eventually opt out. If this or a similar story is the reason for students switching out of science fields, then gender (and perhaps some unobservable characteristics like sensitivity and a taste for family life) may predict switching out of science fields, and ability measures should not play a key role unless they are correlated with those unobservables.

To shed light on these competing explanations, I create three variables capturing the degree to which students switch out of science-related fields. The first is an indicator for whether a student who starts in a science or engineering field switches to finish in a non-science, non-engineering field. The second is the same, but also includes math fields along with science and engineering. The third is the difference in science and engineering credit hours between the student's final major choice and his or her initial major choice. For example, if a student switches from mechanical engineering (66.1 science and engineering credits) to business (4.3 science and engineering credits), this

[27] Of course, this only makes sense if students do not know their true abilities and are initially overconfident.

[28] Arcidiacono (2004), studying both major choice and major switches, finds that switching out of science fields is common, while switching into science fields is rare. He concludes that preferences, rather than abilities, drive most of major choice behavior.

measure would be equal to -61.8.

Switching majors is common in the NLSY data. Among those who start in a science or engineering major, 55% switch out of science or engineering.[29][30] Similarly, 46% of those starting in science, engineering, or math eventually switch out.

Changes of major can be quite dramatic in terms of course content. Among those who begin in a science or engineering major, the average change in science or engineering courses from first major to final major is -26.0, including the non-switchers. If we restrict only to the switchers, the average is -45.8, or about 15 typical courses. When students switch out of science and engineering majors, they are usually switching to majors with very little science content. These are not insignificant changes in major type.

In Table 7, I regress each of these three measures on race and gender. For columns 1 through 3, the sample is those students who begin in the relevant set of majors (either "science or engineering" or "science, engineering, or math"). Column 4 restricts to those who switched out of science or engineering majors. In columns 1 and 2, the regressions are probits, and I report the marginal effects. Columns 3 and 4 are OLS regressions.

In every case (columns 1 through 3), being female is associated with greater switching out of math and science. Men are about 15 percentage points less likely to switch out of science or engineering conditional on starting in science or engineering. The same is true for the broader category that also includes math majors.[31]

In columns 3 and 4, the dependent variable is the change in science and engineering courses from first major to final major, conditional on starting in a science or engineering major. Column 3 shows that, consistent with the results of the first two columns, men have a higher (less negative) change in science and engineering courses, and the

[29] This fraction may seem high, but it is similar to what Stinebrickner and Stinebrickner (2013a) find at Berea College.

[30] If a student switches from one science or engineering field to another, this counts as a 0, or a non-switcher.

[31] It is possible that some "switching" represents double majors who report a different first major in different years. In the NLSY97, about 19% of women and 14% of men report a second major (averaged over all years). If, say, half of double majors are counted as switches by my method, this would imply that I am overestimating the gender gap in major switching by 2.5 percentage points, or by about 20%.

effect is quite large.[32] However, in column 4, we see that among switchers, men actually switched away from science courses to a greater degree than did women.

The race and ethnicity results are less dramatic here. Blacks and Hispanics are more likely to switch out of science and math majors conditional on starting them, for all three measures, although only the Hispanic effects in columns 1 and 2 are significant. If there is a "cultural" reason for switching out of science and engineering majors, then it may be something that applies to both women and minorities. On the other hand, the alternative explanation – that students less proficient in science might initially overestimate their ability but then learn – could plausibly explain why both women and minorities, who score lower in science-related tests on average, switch out of science at higher rates.

Now I perform the "switching out" regressions again, but this time I include first the AFQT and then the entire set of ASVAB scores. If the coefficients on race and gender fall significantly, then one can conclude that pre-college academic factors play a large role in explaining the differential rates of switching.

Table 8 has the results. Columns 1 and 2 follow column 1 in Table 7, columns 3 and 4 follow column 2 in Table 7, and columns 5 and 6 follow column 3 in Table 7.[33] Consistent with the results in Stinebrickner and Stinebrickner (2013a), and consistent with the ability-based explanation, a higher AFQT score negatively predicts switching out of science and math majors. However, women are still significantly more likely to switch out of science majors conditional on starting them, and the magnitudes are the same as in Table 7. While the AFQT coefficients appear to confirm some of the ability explanation, it is clear that adding AFQT alone cannot account for any of the gender gap in switching out of science majors.

In the even-numbered columns, I include all ten ASVAB scores instead of just the AFQT. This has a larger effect on the gender gaps. The gap in the probability of switching out of science is cut by only 22% and 5% (in columns 2 and 4, respectively). The change in science and engineering courses from first major to last major (columns 5 and 6) is cut by about one-fourth when the ASVAB scores are included. It seems clear

[32] Results in column 3 are nearly identical when the sample is instead defined as those who start in a major with a high amount of science credits; the cutoff for "high" has almost no effect on this result.

[33] Here, I exclude the last column of Table 7, which conditioned on switching out.

that including pre-college academic factors has less effect on the gender gap in switching out of science than it does on the gender gap in major choice itself. This implies that most ability sorting into majors occurs at the beginning of college. Switching during college seems mostly driven by non-academic factors.[34]

In terms of the test scores themselves, high math, electronics, and science tests negatively predict switching out of science, while high verbal test scores positively predict switching out of science. This means that students who come into college already good in science and mechanical subjects are likely to stay in science, while those who are good in reading and writing are more likely to eventually find their way out of science. It is clear from these results why the inclusion of test scores would affect the gender coefficient. Interpreting the ASVAB scores as measures of pre-college preparation, this is consistent with the story that the journey from first major to last major "weeds out" some students who are not as prepared in science-related subjects. Further, if students have imperfect and/or biased beliefs about their own ability coming into college, then these results are consistent with students learning about their own ability; those who learn that they are of lower ability in science and math are the ones who switch out, while others stay (Stinebrickner and Stinebrickner 2013a).[35]

While test scores account for some of the gender gap in switching out of science majors, most of the gap remains. The plainest interpretation of these results is that while college preparation accounts for a portion of differential switching behavior between men and women, other factors, perhaps including preferences and the cultures of the fields, are the driving force causing women and minorities to leave science at higher rates. Test scores can account for 67% of the overall gap in science, but at most 22% of the gap in switching behavior. Many women seem to shy away from science completely because of ability deficiencies at the time of college entry. Once they have

[34]One might worry that students enter college having little idea of what they want to do and thus report a major which does represents their intentions only imprecisely. On the other hand, "no major" is an option reported by many students in their first year of college in the data. If instead I classify the *second* major as the actual "first" major and perform the switching analysis, results are broadly similar. The gender gap in switching goes down to about -0.10, and a similar portion of the gap is explained by the ASVAB scores.

[35]Analysis of the NLSY79 and NLSY97 separately (not shown) suggests that the gender gap in the propensity to switch out of STEM has narrowed by about 25% between the two surveys. As mentioned earlier, it is not possible to draw accurate conclusions about how the portion of the gaps explained by skills has changed over time.

started science majors, however, non-academic factors seem to be more important in determining whether they stay.

## 4.3 When do Gender Gaps in Test Scores Appear?

My final set of results focuses on the question of when the test score gaps between men and women appear and how they change with age. In the NLSYs, the ASVAB tests were given to respondents in 1981 (in the NLSY79) and 1999 (in the NLSY97). Given the age structure of the panel, this means that respondents took the tests between ages 15 and 23, allowing me to look at test score gaps by the age of the test-taker.

To make the analysis easier, I here define four composite test scores. "Math" is now the average of the math knowledge and arithmetic scores, "verbal" is the average of word knowledge and paragraph comprehension, "science" is the average of science knowledge and electronics, and "mechanical" is the average of mechanical comprehension and automotive information.[36]

Panel A of Table 9 shows the average gender gap in each composite score in the NLSY79, by the age of the test-taker, measured in standard deviations.[37] The gender gaps do not always move monotonically with the age of the test taker, but there are some clear patterns. On all four composite scores, boys gain with age relative to girls. The math scores show that males scored 0.05 standard deviations *lower* than females at age 16 in this survey, but the gap had reversed to 0.22 standard deviations in favor of males by age 23. The science and mechanical gaps also grew with age in favor of males, from 0.30 to 0.45 (for science) and 0.57 to 0.83 (for mechanical). The verbal score gap was largely stable across age, with boys making slight gains relative to girls.[38]

Panel B shows the same gaps for the NLSY97, where the age range of test takers was 15 to 19. Again, the science and mechcanical score gaps grew substantially with age, from 0.20 to 0.36 for science and 0.21 to 0.52 for mechanical. Note that both of these gaps are smaller in the NLSY97 than in the NLSY79, suggesting that females

[36]These are the same categories used to analyze occupational sorting in Speer (2015).

[37]The measure is the average standardized male score minus the average standardized female score, standardized separately for each quarter-year birth cohort. A measure of 0.5, for example, means that males scored 0.5 standard deviations higher on that test for test takers of that age.

[38]A small number of respondents (less than 2%) were actually age 24 at the time of the tests. I group them with the 23-year-olds here.

have made progress relative to males in these subjects over time. This is also suggested by recent international data that shows boys and girls scoring roughly equally in science (OECD 2015). One again, boys also gain slightly relative to girls in math and verbal scores from ages 15 to 19.[39]

I interpret these patterns as the gaps changing as a cohort of students age, but of course the test-takers at different ages are different birth cohorts. It is possible that what I am picking up are cohort effects and that gaps do not actually change as the same cohort ages. It may be that the widening of the science gap in the NLSY79, for example, is really just evidence of culture becoming more friendly to girls learning science during these years (as the older cohorts, with larger science test score gaps, were born earlier). Given that the gaps in the NLSY97 are smaller than those in the NLSY79 for test-takers of the same age, this is a possibility.

To investigate this, I look at the science and mechanical gaps for the ages which overlap between the two surveys (ages 16, 17, 18, and 19). These gaps closed considerably in the 18 years between the two survey test dates. The science gap closed from 0.3, 0.43, 0.42, and 0.34 in the NLSY79 to 0.19, 0.20, 0.27, and 0.36 in the NLSY97 for ages 16-19. Taking the amount the gap closed in those 18 years, this implies a catch-up rate of 0.007 standard deviations per year. If I take this cohort catch-up effect out of the age gradient observed in the NLSY79 (a widening of 0.15 standard deviations over 7 years), it implies that about 30% of the apparent gap widening by age is actually a cohort effect. This result is similar for the mechanical scores as well. In other words, about 70% of what I observe represents true widening of scores with age.

Because boys are gaining with age relative to girls in all four subjects, one possibility is that age affects test-taking differentially by gender. For instance, Segal (2012) shows that females are more likely to invest effort in tests without performance-based incentives. If older respondents treat the ASVAB tests more seriously than younger respondents, then we would expect boys to gain in all tests as age increases, even if ability is constant with age. This may be part of the story with the ASVAB scores I observe.

However, it is also true that boys' relative gain is larger in science and (especially)

[39] A small number of respondents were actually 14 or 20 at the time of the ASVAB tests (about 1% of the sample each). I group them with the 15-year-olds and 19-year-olds, respectively, in this analysis.

mechanical scores than in, say, the verbal scores. For instance, in the NLSY97, boys gain 0.08, 0.09, 0.16, and 0.31 relative points in math, verbal, science, and mechanical, respectively, from age 15 to 19. Therefore, the growing science and mechanical gaps are likely driven by more than just a general aging effect. Given that the science and mechanical tests are strong predictors of majoring in science-related fields, the origin and timing of these test score gaps is particularly interesting. A possible culprit here is course-taking; boys may take more science- and mechanical-based courses in middle school, high school, and college, which could lead to an increasing advantage in science and mechanical test scores. Here I am primarily interested in the determinants of pre-college ability, so I am most concerned with the effect of middle and high school courses.

To investigate course-taking, I use the NLSY97, which asks about middle and high school (grades 7-12) courses taken by each respondent in each year.[40] My strategy here is threefold. First, I will ask if there are gender gaps in course-taking, and if so, in which types of courses. Second, I will ask if course-taking has a causal effect on ASVAB scores. Third, I will ask if gender gaps in course-taking can explain the gender gaps in ASVAB scores.

I first tally up the courses taken by each respondent. Respondents are asked each year if they have taken certain types of courses between grades 7 and 12 since the last interview – for instance, calculus, physics, algebra, shop, and home economics. I thus have a measure of how many of each type of course each respondent has taken. Table 10 shows the mean number of courses taken by males and females as well as the gender gap (the male mean minus the female mean) for various types of courses. By far the largest gap is in shop class (males take almost an extra half of a shop course on average relative to females), with home economics (0.20 in favor of females) the second-largest. Other course gaps, while sometimes signficant, are small by comparison.

To ask whether course-taking has a causal effect on test scores, I must deal with an issue of reverse causality. Course-taking may influence ability in a subject, but ability in a subject is likely to influence course-taking as well. To deal with this, I take advantage of the structure of the NLSY97. Respondents took the ASVAB tests between ages 15 and 19; age 15 is before most elective course decisions are made, while

[40]The NLSY79 only includes this information for a subset of respondents and only in one year.

age 19 is after these decisions are made. Thus, while I expect there to be a positive relationship between test scores in a field and courses taken in that field, if there is a *causal* effect of test scores on course-taking, this relationship should be stronger for those who took the tests at later ages.[41]

In Table 11, I regress the ASVAB scores that explain the largest portions of the gender gap in major content – the science, mechanical, and auto/shop scores – on the number of courses taken in some relevant fields, separately for those who took the tests at ages 15-16 and those who took the tests at ages 18-19.[42] If there is a causal effect of course-taking on test scores, the effects should be larger for the latter group.

The results suggest a strong causal effect of physics classes (and perhaps chemistry courses) on science and mechanical test scores and of shop and chemistry classes on auto/shop test scores. For instance, the relationship between shop classes and the auto/shop test is twice as strong for the late test-takers, suggesting a causal impact of course on test score. Somewhat surprisingly, though, the other courses do not seem to impact the ASVAB scores.

The final piece of analysis is in Table 12. For the same three ASVAB scores – science, mechanical, and auto/shop – I ask if courses taken can account for any of the gender gap in test scores.[43] The answer to this question is a resounding "no". For science and mechanical tests, including the ASVAB accounts for none of the gender gap; for auto/shop, the ASVAB accounts for only about 7% of the gap. While there are some gender gaps in course-taking, they do not seem to be the driver of the gender gaps in test scores that develop during the teenage years.

From these exercises, I conclude several things. First, for many subjects, there are gender test score gaps at the earliest ages we observe in these surveys, which are ages 15 and 16. Second, these gaps, particularly in science and mechanical ability, widen with age through the teenage years and early twenties. Third, while there are gender differences in course-taking during middle school and high school, and courses taken

[41]The reason is that the effect of ability on course-taking should be present for both groups, but the effect of course-taking on ability should only be present for those who took the tests later. Thus, the relationship between course-taking and test scores should be stronger for the older test takers.

[42]Unfortunately, the NLSY97 asks only about math, science, and vocational-type courses, not about English or other courses that might be linked to verbal test scores.

[43]I restrict here to those who took the ASVAB at age 18 or later, although results are the same for the whole NLSY97 sample.

are predictive of later test scores in some cases, course-taking does not seem to be the driver of the growing gender gaps in test scores.

Abilities at the time of college entry have strong predictive power for college major choices and gender gaps in those choices. It is clear from these data that gender gaps in abilities are present well before age 18, and while they grow with age, this is not primarily due to gender differences in course-taking. The data here do not allow me to pinpoint exactly when the gaps begin to show up, or why they grow with age, but they are present by age 15, and they have explanatory power for college major choices.

# 5 Conclusion

This paper studies the effects of pre-college academic factors on the choice of college major content and college major switching behavior, with a particular focus on gender gaps in major choice. Men and women major in different types of fields: men choose more math-, science-, and business-intensive fields, while women are found more in humanities, social science, and education fields.

Using the ASVAB test scores from the NLSY data sets, I show that pre-college factors can account for a substantial portion of many of these gaps. The ASVAB scores account for 67% of the gap in science, 44% of the gap in engineering, half of the gap in humanities, and 26% of the gender gap in math. Business and education, on the other hand, retain large gender gaps even when controlling for pre-college abilities.

I also study the phenomenon of switching out of STEM majors. Conditional on starting a science or math major, women are substantially more likely to switch out. While a portion of this gap (at most 22%) is explained by the ASVAB scores, it is clear that academic factors explain more of the gap in major choice than of the gap in major-switching behavior. Non-academic factors appear to be more important in determining switching behavior.

These findings have important implications for thinking about competing theories of why women are underrepresented in some fields, particularly science and engineering. Is it ability, or is it culture and discrimination? While these two theories are not mutually exclusive (discrimination in college or the labor market can produce ability differences before college), I have shown here that pre-college abilities are an important factor that cannot be ignored. However, it is also clear that ability cannot explain the full gaps, particularly in switching behavior, and therefore discrimination and the culture of certain fields may have important effects as well.

These gender gaps in ability are present by age 15 at the latest and tend to grow with age, particularly in science and mechanical fields. While course-taking behavior is different for boys and girls, this does not seem to explain the growing gaps in test scores. Finally, in the last few decades, girls have made gains relative to boys in test scores, and the gender gaps in science majors and major-switching behavior have shrunk somewhat over that time. We should expect gains in the proportion of science and engineering degrees going to women, and as test scores become more equal across gender, any gaps that remain may be due to discrimination and culture. Further analysis on more recent data, therefore, is needed to provide more evidence on this question.

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# Tables and Figures

Figure 1:

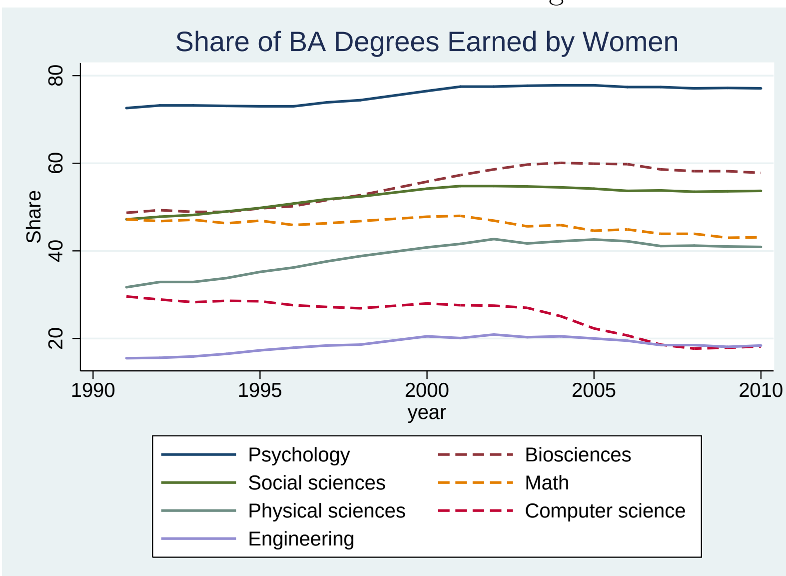


Figure 2:

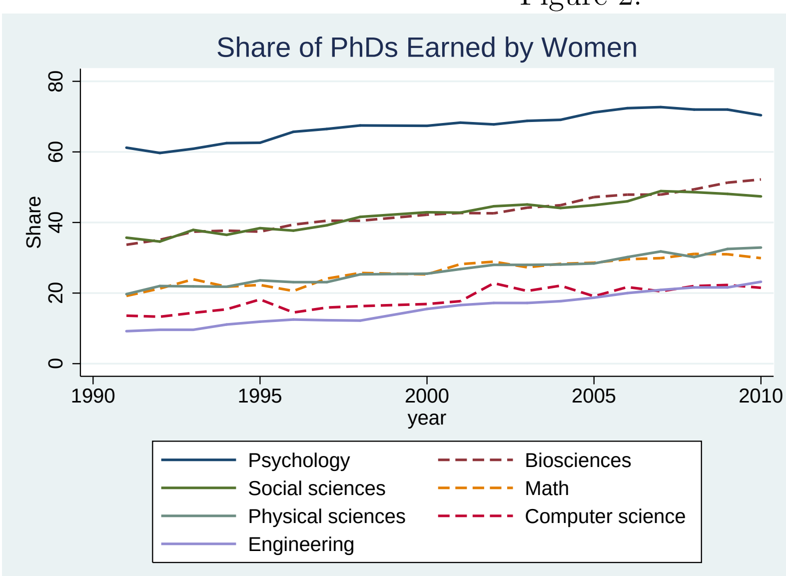

Figure 3:

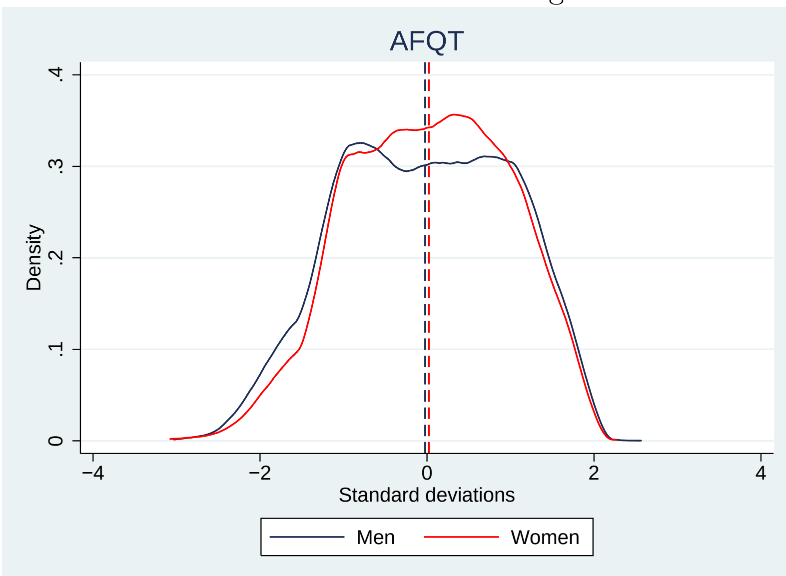


Figure 4:

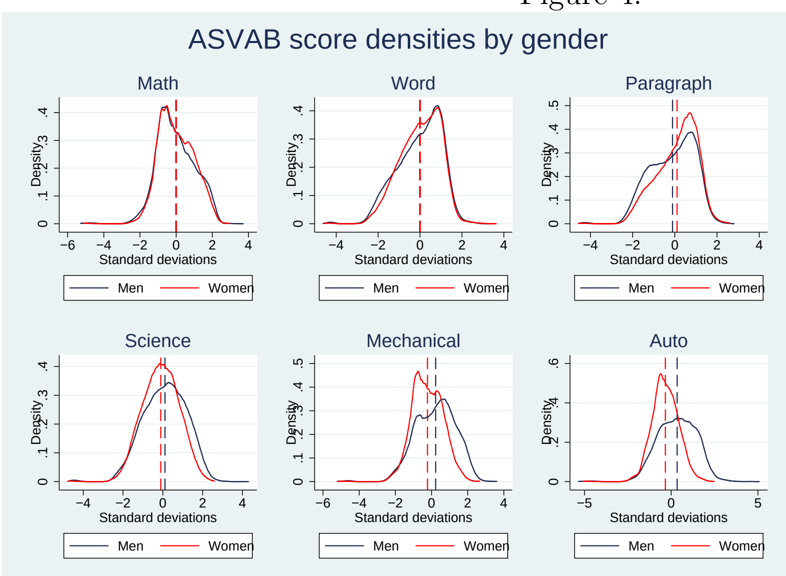

Table 1
Characteristics of College Majors

| Major | SAT M | SAT V | Math | Humanities | Business | social science | Education | Sci/engineering |
|---|---|---|---|---|---|---|---|---|
| Mathematics | 591.7 | 538.2 | 29.9 | 16.4 | 3.2 | 14.3 | 8.2 | 13.7 |
| Physics | | | 17.9 | 16.1 | 0.2 | 12.2 | 1.5 | 46.5 |
| Civil Engineering | 597.1 | 560.1 | 11.3 | 7.8 | 0.6 | 9.0 | 0.3 | 73.0 |
| Chemical Engineering | | | 10.6 | 8.4 | 0.9 | 7.5 | 0.5 | 76.5 |
| Engineering Tech | 542.3 | 490.5 | 8.8 | 10.5 | 5.3 | 9.2 | 1.4 | 30.6 |
| Mechanical Engineering | 613.3 | 565.7 | 12.7 | 8.6 | 0.6 | 8.7 | 0.3 | 66.1 |
| Electrical Engineering | 606.0 | 570.7 | 12.5 | 8.7 | 3.9 | 8.4 | 0.3 | 66.5 |
| Other Engineering | 609.6 | 557 | 13.6 | 9.5 | 3.3 | 9.1 | 0.3 | 61.9 |
| Chemistry | 603.9 | 596.7 | 12.1 | 15.7 | 0.7 | 12.5 | 0.6 | 57.2 |
| Computer and Info Tech | 582.3 | 556.2 | 11.9 | 12.6 | 11.8 | 13.1 | 0.4 | 11.1 |
| Earth Sciences | | | 8.0 | 11.8 | 1.1 | 17.3 | 5.1 | 55.4 |
| Secondary Education | | | 7.6 | 16.5 | 2.5 | 21.8 | 28.6 | 13.5 |
| Computer Programming | | | 6.4 | 12.3 | 22.3 | 13.8 | 0.2 | 5.8 |
| Biological Sciences | 577.1 | 575.4 | 6.2 | 15.3 | 0.9 | 14.0 | 2.1 | 56.1 |
| Economics | 597.1 | 573.1 | 6.0 | 19.0 | 16.2 | 41.6 | 0.6 | 6.3 |
| Business/Med Support | | | 4.9 | 12.7 | 25.7 | 16.5 | 1.1 | 6.1 |
| General Science | | | 4.8 | 16.0 | 2.8 | 16.5 | 12.8 | 19.9 |
| Accounting | 570.8 | 534.1 | 4.3 | 11.3 | 47.6 | 14.9 | 0.3 | 3.7 |
| Architecture | | | 4.4 | 10.0 | 0.7 | 10.9 | 0.0 | 9.5 |
| Education/Library Sci | 488.3 | 495.9 | 4.2 | 13.6 | 0.8 | 15.7 | 45.3 | 7.1 |
| Business | 522.3 | 510.1 | 4.2 | 11.6 | 39.4 | 15.9 | 0.7 | 4.3 |
| Agriculture/Ag Science | 546.3 | 549.2 | 4.1 | 8.6 | 15.4 | 12.7 | 1.0 | 21.1 |
| Family/Consumer Science | 499.7 | 503.6 | 3.7 | 11.3 | 5.3 | 18.0 | 9.7 | 8.4 |
| Psychology | 530.1 | 540.1 | 3.4 | 17.8 | 2.4 | 45.8 | 3.3 | 8.2 |
| Foreign Language | 540.2 | 583.9 | 3.3 | 47.1 | 2.8 | 19.3 | 6.9 | 6.9 |
| Music/Speech/Drama | 539.1 | 574.7 | 3.1 | 21.4 | 2.6 | 13.9 | 4.7 | 6.5 |
| Fitness and Nutrition | 519.5 | 518.2 | 3.6 | 9.9 | 3.4 | 14.1 | 6.5 | 19.9 |
| Leisure Studies | 472.2 | 459.8 | 3.1 | 11.2 | 6.3 | 14.5 | 4.6 | 9.7 |
| Communications | 511.9 | 537.4 | 3.0 | 23.5 | 5.1 | 24.3 | 1.6 | 5.8 |
| Other Med/Health Services | 524.9 | 519.2 | 3.0 | 9.1 | 1.7 | 9.7 | 2.7 | 19.4 |
| Other Social Science | 513.6 | 525.8 | 3.0 | 16.6 | 2.0 | 42.7 | 3.1 | 7.2 |
| Area studies | 547.5 | 578 | 2.9 | 28.5 | 2.3 | 40.2 | 2.0 | 6.3 |
| Literature and Writing | 540.3 | 591.8 | 2.8 | 51.9 | 1.2 | 19.2 | 4.5 | 6.1 |
| Political Science | 541.5 | 570.6 | 2.7 | 22.9 | 2.3 | 52.8 | 1.1 | 6.2 |
| History | 557.9 | 594.6 | 2.5 | 22.1 | 1.4 | 50.0 | 5.2 | 6.0 |
| Art History/Fine Arts | 555.3 | 592.2 | 2.3 | 31.3 | 1.0 | 13.5 | 3.9 | 6.9 |
| Law/Public Admin. | | | 2.2 | 12.7 | 9.3 | 21.3 | 0.3 | 3.4 |
| Social Work | 460.3 | 486.7 | 2.2 | 11.4 | 0.6 | 28.0 | 1.6 | 5.2 |
| Philosophy/Religion | 567.2 | 595.1 | 2.1 | 35.2 | 0.8 | 20.9 | 3.7 | 5.7 |
| Journalism | | | 2.1 | 21.2 | 4.3 | 29.8 | 0.4 | 5.5 |
| Public health | | | 1.9 | 7.3 | 0.8 | 9.1 | 1.3 | 26.5 |
| Nursing | 488.2 | 497.1 | 1.4 | 9.2 | 0.7 | 9.6 | 0.7 | 13.0 |

Note: SAT M and SAT V are the average SAT scores in each major, as measured in the Baccalaureate and Beyond data set. Some sample sizes in that data set are small, and therefore the SAT scores for those majors are left blank. The next six columns report the average number of credit hours in each subject taken by a student with the given major.

Table 2

Summary Statistics

| | n | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Male | 2,462 | 0.44 | 0.50 | 0 | 1 |
| Black | 2,462 | 0.17 | 0.38 | 0 | 1 |
| Hispanic | 2,462 | 0.12 | 0.32 | 0 | 1 |
| Final years of education | 2,462 | 17.07 | 1.30 | 16 | 20 |
| Science major | 2,462 | 0.06 | 0.23 | 0 | 1 |
| Engineering major | 2,462 | 0.06 | 0.24 | 0 | 1 |
| ASVAB tests: | | | | | |
| Math knowledge | 2,462 | 0.80 | 0.81 | -2.14 | 3.71 |
| Arithmetic | 2,462 | 0.70 | 0.84 | -2.50 | 3.22 |
| Word knowledge | 2,462 | 0.66 | 0.79 | -2.49 | 3.64 |
| Paragraph comprehension | 2,462 | 0.71 | 0.77 | -2.34 | 2.62 |
| Science | 2,462 | 0.66 | 0.87 | -2.48 | 4.30 |
| Mechanical | 2,467 | 0.52 | 0.87 | -2.42 | 3.61 |
| Automotive | 2,469 | 0.27 | 0.88 | -2.66 | 3.52 |
| Electronics | 2,470 | 0.49 | 0.89 | -2.38 | 5.24 |
| Numerical operations | 2,453 | 0.59 | 0.85 | -2.82 | 4.01 |
| Coding speed | 2,453 | 0.52 | 0.91 | -5.06 | 3.44 |

The sample, combined from the NLSY79 and 97, is those with at least 16 years of education who took the ASVAB tests before age 19 and who have a valid major observation. The ASVAB scores are given in standard deviations, where the standardization is done on the entire NLSY sample (separately for NLSY79 and NLSY97), including those who do not attend college.

Table 3
Race and Gender Gaps in College Majors

| | (1) Math | (2) Humanities | (3) Business | (4) Soc. Studies | (5) Education | (6) Sci/Engin | (7) SAT Math | (8) Engineering |
|---|---|---|---|---|---|---|---|---|
| Male | 1.657*** | -1.065*** | 2.973*** | -1.035** | -4.673*** | 4.882*** | 20.112*** | 0.087*** |
| | (0.166) | (0.370) | (0.634) | (0.513) | (0.545) | (0.703) | (1.424) | (0.010) |
| Black | -0.246 | -0.752 | -0.068 | 1.154* | 0.273 | -1.665* | -4.353** | -0.017* |
| | (0.222) | (0.494) | (0.846) | (0.685) | (0.727) | (0.938) | (1.911) | (0.009) |
| Hispanic | -0.169 | -0.561 | -1.578 | 2.197*** | -0.289 | -0.827 | -2.050 | -0.009 |
| | (0.258) | (0.575) | (0.986) | (0.798) | (0.847) | (1.092) | (2.213) | (0.010) |
| Constant | 4.270*** | 17.296*** | 10.558*** | 21.039*** | 8.734*** | 11.899*** | 527.933*** | |
| | (0.124) | (0.277) | (0.475) | (0.384) | (0.408) | (0.526) | (1.054) | |
| Observations | 2,462 | 2,462 | 2,462 | 2,462 | 2,462 | 2,462 | 2,266 | 2,679 |
| R-squared | 0.040 | 0.004 | 0.010 | 0.006 | 0.030 | 0.022 | 0.085 | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The sample, combined from the NLSY79 and 97, is those with at least 16 years of education who took the ASVAB tests before age 19 and who have a valid major observation. “Black” means non-Hispanic black. The omitted category for race/ethnicity is non-black non-Hispanics. The dependent variables in columns 1-7 represent averages of students in each major, as taken from the Baccalaureate and Beyond and reported by the Department of Education. Columns 1-7 are estimated using Ordinary Least Squares. Column 8 is a probit regression, and the results I report are the marginal effects of each variable.

Table 4
Test Scores and College Majors

| | (1) Math | (2) Humanities | (3) Business | (4) Soc. Studies | (5) Education | (6) Sci/Engin | (7) SAT Math | (8) Engineering |
|---|---|---|---|---|---|---|---|---|
| Automotive | 0.040 | -1.019*** | 1.353*** | -0.839** | -0.956** | 0.579 | 0.846 | 0.005 |
| | (0.117) | (0.256) | (0.448) | (0.362) | (0.389) | (0.487) | (1.008) | (0.005) |
| Arithmetic | 0.662*** | -0.549 | 1.845*** | -0.900* | -0.816 | 0.773 | 4.296*** | 0.027*** |
| | (0.172) | (0.375) | (0.656) | (0.530) | (0.570) | (0.714) | (1.476) | (0.008) |
| Coding Speed | -0.150 | -0.254 | 1.373*** | -0.050 | -0.261 | -0.642 | -0.755 | -0.005 |
| | (0.108) | (0.235) | (0.411) | (0.332) | (0.357) | (0.447) | (0.922) | (0.005) |
| Electronics | 0.549*** | -0.199 | 0.261 | -0.448 | -0.953** | 2.054*** | 4.537*** | 0.017*** |
| | (0.138) | (0.301) | (0.526) | (0.425) | (0.457) | (0.572) | (1.182) | (0.005) |
| Science | 0.274* | 0.420 | -1.665*** | -0.186 | -0.154 | 2.453*** | 5.695*** | 0.018*** |
| | (0.165) | (0.361) | (0.632) | (0.511) | (0.549) | (0.688) | (1.421) | (0.007) |
| Mechanical | 0.307** | -0.462 | -0.209 | -0.470 | -0.187 | 2.378*** | 3.989*** | 0.020*** |
| | (0.142) | (0.309) | (0.541) | (0.437) | (0.470) | (0.588) | (1.221) | (0.006) |
| Math | 0.559*** | -1.412*** | 0.388 | -1.325** | -0.859 | 2.418*** | 3.191** | 0.007 |
| | (0.170) | (0.371) | (0.649) | (0.524) | (0.564) | (0.706) | (1.464) | (0.008) |
| Numerical Ops | -0.083 | 0.006 | 0.490 | 0.080 | 0.217 | -0.313 | -1.574 | -0.004 |
| | (0.121) | (0.264) | (0.461) | (0.372) | (0.401) | (0.502) | (1.034) | (0.005) |
| Paragraphs | -0.464*** | 1.480*** | -2.943*** | 0.439 | 1.505*** | -0.660 | -3.854*** | -0.005 |
| | (0.163) | (0.355) | (0.621) | (0.502) | (0.540) | (0.676) | (1.394) | (0.007) |
| Word Knowledge | -0.924*** | 2.626*** | -0.738 | 2.718*** | -0.345 | -4.533*** | -4.441*** | -0.047*** |
| | (0.171) | (0.373) | (0.653) | (0.527) | (0.567) | (0.710) | (1.461) | (0.008) |
| Constant | 4.490*** | 15.791*** | 12.372*** | 21.369*** | 8.026*** | 11.221*** | 528.980*** | |
| | (0.123) | (0.268) | (0.469) | (0.379) | (0.407) | (0.510) | (1.062) | |
| Observations | 2,442 | 2,442 | 2,442 | 2,442 | 2,442 | 2,442 | 2,247 | 2,658 |
| R-squared | 0.066 | 0.058 | 0.031 | 0.025 | 0.028 | 0.080 | 0.103 | |

Table 5
Effect of Test Scores on College Major Gender Gap: Coefficients on Male

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Major content | No test scores | AFQT included | All ASVAB included | % Explained by AFQT | % Explained by ASVAB |
| Mathematics | 1.657*** | 1.602*** | 1.222*** | 3.3% | 26.3% |
| | (0.166) | (0.544) | (0.192) | | |
| Humanities | -1.065*** | -1.188*** | -0.542 | -11.5% | 49.1% |
| | (0.370) | (0.370) | (0.422) | | |
| Business | 2.973*** | 3.113*** | 3.483*** | -4.7% | -17.2% |
| | (0.634) | (0.635) | (0.734) | | |
| social science | -1.035** | -1.060** | -0.139 | -2.4% | 86.6% |
| | (0.513) | (0.514) | (0.596) | | |
| Education | -4.673*** | -4.439*** | -3.897*** | 5.0% | 16.6% |
| | (0.545) | (0.542) | (0.636) | | |
| Science/Engineering | 4.882*** | 4.543*** | 1.611** | 6.9% | 67.0% |
| | (0.703) | (0.699) | (0.801) | | |
| SAT Math | 20.112*** | 19.144*** | 15.614*** | 4.8% | 22.4% |
| | (1.424) | (1.402) | (1.628) | | |
| Engineering major (probit) | 0.087*** | 0.082*** | 0.048*** | 5.7% | 44.8% |
| | (0.010) | (0.010) | (0.009) | | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The sample, combined from the NLSY79 and 97, is those with at least 16 years of education who took the ASVAB tests before age 19 and who have a valid major observation. Each cell in columns 1-3 represents a different regression and reports the coefficient on "Male" from a regression of the dependent variable (given under "Major content") on gender, race/ethnicity, and the AFQT or ASVAB scores as appropriate. Column 4 is calculated by comparing the coefficients in columns 1 and 2. Column 5 is calculated by comparing columns 1 and 3.

Table 6
Effect of Test Scores on College Major Racial Gap: Coefficients on Black

| Major content | (1) No test scores | (2) AFQT included | (3) All ASVAB included | (4) % Explained by AFQT | (5) % Explained by ASVAB |
|---|---|---|---|---|---|
| Mathematics | -0.246 | 0.198 | 0.395 | 180.5% | 260.6% |
| | (0.222) | (0.242) | (0.245) | | |
| Humanities | -0.752 | 0.241 | -0.227 | 132.0% | 69.8% |
| | (0.494) | (0.539) | (0.540) | | |
| Business | -0.068 | -1.203 | -1.374 | -1669.1% | -1920.6% |
| | (0.846) | (0.925) | (0.939) | | |
| social science | 1.154* | 1.358* | 0.565 | -17.7% | 51.0% |
| | (0.684) | (0.750) | (0.762) | | |
| Education | 0.273 | -1.626** | -1.550** | 695.6% | 667.8% |
| | (0.727) | (0.790) | (0.813) | | |
| Science/Engineering | -1.665* | 1.081 | 2.737*** | 164.9% | 264.4% |
| | (0.938) | (1.018) | (0.1.025) | | |
| SAT Math | -4.353** | 3.239 | 5.283** | 174.4% | 221.4% |
| | (1.911) | (2.050) | (2.088) | | |
| Engineering major (probit) | -0.017* | 0.001 | 0.017 | 105.9% | 200.0% |
| | (0.009) | (0.012) | (0.013) | | |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The sample, combined from the NLSY79 and 97, is those with at least 16 years of education who took the ASVAB tests before age 19 and who have a valid major observation. Each cell in columns 1-3 represents a different regression and reports the coefficient on "Black" from a regression of the dependent variable (given under "Major content") on gender, race/ethnicity, and the AFQT or ASVAB scores as appropriate. Column 4 is calculated by comparing the coefficients in columns 1 and 2. Column 5 is calculated by comparing columns 1 and 3.

Table 7
Switching Out of Science-Related Majors

| | (1) Switch from sci/engineering | (2) Switch from sci/engin/math | (3) Change in sci/engin courses | (4) Change in sci/engin courses |
|---|---|---|---|---|
| Male | -0.147*** | -0.145*** | 5.587** | -4.163*** |
| | (0.049) | (0.048) | (2.540) | (1.067) |
| Black | 0.033 | 0.102 | -1.923 | 1.440 |
| | (0.072) | (0.069) | (3.682) | (1.507) |
| Hispanic | 0.143* | 0.131* | -6.436 | 1.432 |
| | (0.076) | (0.075) | (3.906) | (1.497) |
| Constant | | | -24.524*** | -47.275*** |
| | | | (2.117) | (0.844) |
| Observations | 417 | 449 | 400 | 183 |
| R-squared | | | 0.020 | 0.091 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The sample, combined from the NLSY79 and 97, is those with at least 16 years of education who took the ASVAB tests before age 19 and who have a valid major observation. Columns 1 and 3 restrict to those who first reported a science or engineering major. Column 2 restricts to those who first reported a science, engineering, or math major. Column 4 restricts to those who first reported a science or engineering major and later reported a non-science, non-engineering major. Columns 1 and 2 are probit regressions, where I report the marginal effects of each variable, and columns 3 and 4 are estimated using OLS.

Table 8
Switching Out of Science-Related Majors, with Test Scores

| | (1) Switch from sci/engin | (2) Switch from sci/engin | (3) Switch from sci/engin/math | (4) Switch from sci/engin/math | (5) Change in sci/engin courses | (6) Change in sci/engin courses |
|---|---|---|---|---|---|---|
| Male | -0.148*** | -0.116* | -0.148*** | -0.141** | 5.483** | 4.023 |
| | (0.050) | (0.060) | (0.048) | (0.058) | (2.507) | (2.963) |
| Black | -0.052 | -0.067 | -0.022 | -0.012 | 3.919 | 3.838 |
| | (0.078) | (0.080) | (0.078) | (0.080) | (4.021) | (4.060) |
| Hispanic | 0.101 | 0.081 | 0.072 | 0.063 | -3.514 | -3.652 |
| | (0.079) | (0.082) | (0.079) | (0.082) | (3.950) | (4.067) |
| Test scores: | | | | | | |
| AFQT | -0.103** | | -0.144*** | | 7.097*** | |
| | (0.041) | | (0.040) | | (2.091) | |
| Automotive | | 0.093** | | 0.079** | | -4.710*** |
| | | (0.037) | | (0.036) | | (1.819) |
| Arithmetic | | -0.003 | | -0.009 | | -0.208 |
| | | (0.056) | | (0.055) | | (2.727) |
| Coding | | 0.044 | | 0.039 | | -2.188 |
| | | (0.036) | | (0.033) | | (1.719) |
| Electronics | | -0.076* | | -0.044 | | 3.223 |
| | | (0.041) | | (0.040) | | (1.997) |
| Science | | -0.065 | | -0.057 | | 3.686 |
| | | (0.055) | | (0.053) | | (2.683) |
| Mechanical | | -0.041 | | -0.018 | | 1.825 |
| | | (0.045) | | (0.043) | | (2.165) |
| Math | | -0.108* | | -0.106* | | 6.039** |
| | | (0.057) | | (0.056) | | (2.741) |
| Numerical Ops | | 0.015 | | 0.005 | | -0.301 |
| | | (0.041) | | (0.039) | | (2.005) |
| Paragraphs | | 0.015 | | -0.025 | | 0.306 |
| | | (0.055) | | (0.053) | | (2.780) |
| Words | | 0.059 | | 0.026 | | -2.788 |
| | | (0.054) | | (0.052) | | (2.648) |
| Constant | | | | | -34.576*** | -33.373*** |
| | | | | | (3.625) | (3.252) |
| Observations | 417 | 415 | 449 | 447 | 400 | 398 |
| R-squared | | | | | 0.048 | 0.081 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The sample, combined from the NLSY79 and 97, is those with at least 16 years of education who took the ASVAB tests before age 19 and who have a valid major observation. Columns 1, 2, 5, and 6 restrict to those who first reported a science or engineering major. Columns 3 and 4 restrict to those who first reported a science, engineering, or math major. Columns 1-4 are probit regressions, where I report the marginal effects of each variable, and columns 5 and 6 are estimated using OLS. The ASVAB scores are given in standard deviations, where the standardization is done on the entire NLSY sample (separately for NLSY79 and NLSY97), including those who do not attend college.

Table 9

Gender Gaps in Test Scores (Male minus Female), by Age

| | (1) Math | (2) Verbal | (3) Science | (4) Mechanical |
|---|---|---|---|---|
| Panel A: NLSY79 | | | | |
| Age at time of test: | | | | |
| 16 | -0.05 | -0.20 | 0.30 | 0.57 |
| 17 | 0.13 | -0.06 | 0.43 | 0.70 |
| 18 | 0.10 | -0.12 | 0.42 | 0.70 |
| 19 | 0.08 | -0.20 | 0.34 | 0.65 |
| 20 | 0.09 | -0.11 | 0.38 | 0.68 |
| 21 | 0.17 | -0.07 | 0.44 | 0.76 |
| 22 | 0.21 | -0.10 | 0.41 | 0.71 |
| 23 | 0.22 | -0.11 | 0.45 | 0.83 |
| Panel B: NLSY97 | | | | |
| Age at time of test: | | | | |
| 15 | -0.04 | -0.11 | 0.20 | 0.21 |
| 16 | -0.07 | -0.11 | 0.19 | 0.30 |
| 17 | -0.10 | -0.18 | 0.20 | 0.31 |
| 18 | -0.07 | -0.13 | 0.27 | 0.49 |
| 19 | 0.04 | -0.02 | 0.36 | 0.52 |

The sample is the whole NLSY79 (panel A) and NLSY97 (panel B), excluding those without valid ASVAB scores. The ASVAB scores are given in standard deviations, where the standardization is done on the entire NLSY sample (separately for NLSY79 and NLSY97), including those who do not attend college. The measure reported is the average male score within that age group minus the average female score within that age range. "Math" is now the average of the math knowledge and arithmetic ASVAB scores, "verbal" is the average of word knowledge and paragraph comprehension, "science" is the average of science knowledge and electronics, and "mechanical" is the average of mechanical comprehension and automotive information.

Table 10

Grade 7-12 Courses Taken by Gender, NLSY97

| Field | (1) Males | (2) Females | (3) Gender gap |
|---|---|---|---|
| Algebra 1 | 1.58 | 1.55 | 0.03* |
| Algebra 2 | 0.79 | 0.84 | -0.05*** |
| Geometry | 0.93 | 0.99 | -0.06*** |
| Trigonometry | 0.24 | 0.27 | -0.03*** |
| Pre-calculus | 0.25 | 0.29 | -0.03*** |
| Calculus | 0.11 | 0.10 | 0.01** |
| Other advanced math | 0.07 | 0.08 | -0.02*** |
| Biology | 1.36 | 1.34 | 0.03 |
| Chemistry | 0.92 | 1.01 | -0.09*** |
| Physics | 0.52 | 0.47 | 0.05*** |
| Other science | 0.91 | 0.93 | 0.02 |
| Computer literacy | 0.54 | 0.51 | 0.03** |
| Computer programming | 0.37 | 0.30 | 0.07*** |
| Word processing | 0.60 | 0.61 | -0.01 |
| Other computer | 0.51 | 0.51 | 0.00 |
| Shop | 0.64 | 0.19 | 0.45*** |
| Home economics | 0.37 | 0.57 | -0.20*** |

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The sample is the NLSY97. Course measurements are the mean number of courses in each field by males and females, respectively. The gender gap is the male mean minus the female mean.

Table 11

Effect of Courses on ASVAB Scores, NLSY97

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Science test | | Mechanical test | | Auto/Shop test | |
| | Young takers | Older takers | Young takers | Older takers | Young takers | Older takers |
| Shop courses | 0.081*** | 0.022 | 0.122*** | 0.114*** | 0.159*** | 0.292*** |
| | (0.019) | (0.029) | (0.019) | (0.030) | (0.019) | (0.031) |
| Physics courses | -0.005 | 0.101*** | -0.040 | 0.087*** | 0.002 | 0.024 |
| | (0.025) | (0.025) | (0.025) | (0.026) | (0.026) | (0.027) |
| Chemistry courses | 0.129*** | 0.213*** | 0.135*** | 0.143*** | 0.033 | 0.053** |
| | (0.023) | (0.021) | (0.023) | (0.022) | (0.024) | (0.023) |
| Precal courses | 0.375*** | 0.342*** | 0.355*** | 0.297*** | 0.260*** | 0.156*** |
| | (0.034) | (0.036) | (0.034) | (0.037) | (0.035) | (0.038) |
| Calculus courses | 0.471*** | 0.379*** | 0.415*** | 0.212*** | 0.246*** | 0.176*** |
| | (0.049) | (0.056) | (0.049) | (0.058) | (0.051) | (0.060) |
| Constant | -0.310*** | -0.468*** | -0.309*** | -0.368*** | -0.223*** | -0.225*** |
| | (0.028) | (0.033) | (0.028) | (0.034) | (0.029) | (0.035) |
| Observations | 2,865 | 2,799 | 2,833 | 2,778 | 2,837 | 2,781 |
| R-squared | 0.137 | 0.164 | 0.122 | 0.093 | 0.063 | 0.049 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The sample is the NLSY97. Course totals are the number of courses in each field taken by the respondent. Test scores are the ASVAB scores, given in standard deviations. The sample in columns 1, 3, and 5 is restricted to those who took the ASVAB at age 16 or younger. The sample in columns 2, 4, and 6 is restricted to those who took the ASVAB at age 18 or older.

Table 12
Effect of Courses on Gender Gaps in ASVAB Scores, NLSY97

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Science test | | Mechanical test | | Auto/Shop test | |
| | No courses | Courses included | No courses | Courses included | No courses | Courses included |
| Male | 0.165*** | 0.217*** | 0.350*** | 0.366*** | 0.614*** | 0.572*** |
| | (0.033) | (0.031) | (0.033) | (0.033) | (0.033) | (0.034) |
| Black | -1.021*** | -0.885*** | -1.038*** | -0.931*** | -0.847*** | -0.785*** |
| | (0.040) | (0.036) | (0.039) | (0.038) | (0.039) | (0.040) |
| Hispanic | -0.807*** | -0.646*** | -0.663*** | -0.539*** | -0.639*** | -0.569*** |
| | (0.044) | (0.040) | (0.044) | (0.042) | (0.044) | (0.044) |
| Constant | 0.338*** | -0.159*** | 0.226*** | -0.086* | 0.043 | -0.004 |
| | (0.028) | (0.047) | (0.028) | (0.050) | (0.028) | (0.052) |
| Observations | 2,799 | 2,799 | 2,778 | 2,778 | 2,781 | 2,781 |
| R-squared | 0.228 | 0.400 | 0.242 | 0.344 | 0.247 | 0.281 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The sample is the NLSY97. Course totals (includd in columns 2, 4, and 6) are the number of courses in each field taken by the respondent. Test scores are the ASVAB scores, given in standard deviations. The sample is restricted to those who took the ASVAB at age 18 or older.

Appendix Table 1

Race and Gender Gaps in College Majors (Whole NLSY79, including later test takers)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Math | Humanities | Business | Soc. Studies | Education | Sci/Engin | SAT Math | Engineering |
| Male | 1.313*** | -0.123 | 3.515*** | -0.428 | -6.167*** | 6.240*** | 22.355*** | 0.101*** |
| | (0.164) | (0.320) | (0.702) | (0.403) | (0.641) | (0.725) | (1.630) | (0.010) |
| Black | -0.133 | -0.960** | 0.568 | 1.233** | -1.524* | -1.033 | -2.711 | -0.002 |
| | (0.211) | (0.411) | (0.901) | (0.517) | (0.823) | (0.930) | (2.118) | (0.011) |
| Hispanic | 0.214 | -0.382 | -2.106* | -0.206 | 1.350 | 2.071* | -0.009 | 0.026 |
| | (0.272) | (0.531) | (1.164) | (0.669) | (1.063) | (1.202) | (2.692) | (0.017) |
| Constant | 4.278*** | 15.000*** | 12.137*** | 18.089*** | 11.386*** | 10.616*** | 520.661*** | |
| | (0.123) | (0.241) | (0.528) | (0.303) | (0.482) | (0.545) | (1.214) | |
| Observations | 2,327 | 2,327 | 2,327 | 2,327 | 2,327 | 2,327 | 1,936 | 2,405 |
| R-squared | 0.028 | 0.002 | 0.012 | 0.003 | 0.040 | 0.033 | 0.090 | |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The sample is the NLSY79 and includes those with at least 16 years of education and who have a valid major observation. “Black” means non-Hispanic black. The omitted category for race/ethnicity is non-black non-Hispanics. The dependent variables in columns 1-7 represent averages of students in each major, as taken from the Baccalaureate and Beyond and reported by the Department of Education. Columns 1-7 are estimated using Ordinary Least Squares. Column 8 is a probit regression, and the results I report are the marginal effects of each variable.

Appendix Table 2
Race and Gender Gaps in College Majors (Whole NLSY97, including later test takers)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Math | Humanities | Business | Soc. Studies | Education | Sci/Engin | SAT Math | Engineering |
| Male | 1.875*** | -1.098** | 3.344*** | -1.315** | -4.655*** | 4.348*** | 21.007*** | 0.077*** |
| | (0.186) | (0.430) | (0.695) | (0.608) | (0.602) | (0.782) | (1.550) | (0.010) |
| Black | -0.135 | -0.481 | 0.118 | 1.217 | 0.029 | -2.263** | -2.969 | -0.020** |
| | (0.254) | (0.586) | (0.948) | (0.830) | (0.820) | (1.067) | (2.113) | (0.009) |
| Hispanic | -0.287 | -0.699 | -0.550 | 2.252** | -0.595 | -2.296* | -3.439 | -0.021** |
| | (0.286) | (0.660) | (1.067) | (0.934) | (0.924) | (1.202) | (2.403) | (0.009) |
| Constant | 4.135*** | 17.797*** | 9.539*** | 21.909*** | 8.453*** | 12.336*** | 528.169*** | |
| | (0.137) | (0.317) | (0.512) | (0.449) | (0.444) | (0.577) | (1.134) | |
| Observations | 1,921 | 1,921 | 1,921 | 1,921 | 1,921 | 1,921 | 1,816 | 2,124 |
| R-squared | 0.052 | 0.004 | 0.012 | 0.006 | 0.031 | 0.021 | 0.096 | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The sample is the NLSY97 and includes those with at least 16 years of education and who have a valid major observation. "Black" means non-Hispanic black. The omitted category for race/ethnicity is non-black non-Hispanics. The dependent variables in columns 1-7 represent averages of students in each major, as taken from the Baccalaureate and Beyond and reported by the Department of Education. Columns 1-7 are estimated using Ordinary Least Squares. Column 8 is a probit regression, and the results I report are the marginal effects of each variable.

Appendix Table 3

Effect of Test Scores and Noncognitive Measures on College Major Gender Gaps: Coefficients on Male (NLSY79 Only)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Major content | No scores | AFQT | Noncog. | All ASVAB | ASVAB and Noncog. | % Expl. by AFQT | % Expl. by Noncog. | % Expl. by ASVAB | % Expl. by ASVAB and Noncog. |
| Math | 0.882** | 0.785** | 0.862** | 0.056 | 0.027 | 11.0% | 2.2% | 93.7% | 97.0% |
| | (0.368) | (0.367) | (0.373) | (0.470) | (0.475) | | | | |
| Human. | -0.512 | -0.537 | -0.580 | 1.310 | 1.278 | -4.9% | -13.3% | 355.9% | 349.3% |
| | (0.699) | (0.702) | (0.708) | (0.895) | (0.906) | | | | |
| Bus. | 1.107 | 1.089 | 1.157 | 2.609 | 2.639 | 1.6% | -4.6% | -135.6% | -138.4% |
| | (1.478) | (1.486) | (1.495) | (1.886) | (1.903) | | | | |
| Soc. Sci. | 0.555 | 0.579 | 0.509 | 2.307** | 2.338** | -4.2% | 8.3% | -315.4% | -321.0% |
| | (0.860) | (0.864) | (0.865) | (1.106) | (1.110) | | | | |
| Educ. | -5.032*** | -4.776*** | -5.202*** | -3.925** | -4.046** | 5.08% | -3.38% | 22.0% | 19.6% |
| | (1.258) | (1.258) | (1.266) | (1.612) | (1.617) | | | | |
| Sci/Eng | 6.677*** | 6.301*** | 6.658*** | 1.412 | 1.308 | 5.63% | 0.3% | 78.8% | 80.4% |
| | (1.585) | (1.582) | (1.607) | (1.993) | (2.017) | | | | |
| SAT Math | 17.300*** | 16.241*** | 16.927*** | 11.309** | 10.942** | 6.1% | 2.2% | 34.6% | 36.8% |
| | (3.501) | (3.473) | (3.539) | (4.537) | (4.582) | | | | |
| Engineering | 0.113*** | 0.106*** | 0.113*** | 0.037 | 0.038 | 6.6% | 0.0% | 67.3% | 66.8% |
| | (0.024) | (0.023) | (0.024) | (0.027) | (0.027) | | | | |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The sample, restricted to the NLSY79, is those with at least 16 years of education who took the ASVAB tests before age 19 and who have a valid major observation. Each cell in columns 1-5 represents a different regression and reports the coefficient on "Male" from a regression of the dependent variable (given under "Major content") on gender, race/ethnicity, and the AFQT, ASVAB scores, and/or noncognitive skill measures as appropriate. The noncognitive skill measures are the Rotter Locus of Control Score and the Rosenberg Self-Esteem Score. Column 6 is calculated by comparing the coefficients in columns 1 and 2. Column 7 is calculated by comparing columns 1 and 3. Column 8 is calculated by comparing columns 1 and 4. Column 9 is calculated by comparing columns 1 and 5.

Appendix Table 4
Effect of Test Scores on College Major Gender Gaps: Coefficients on Male (NLSY97 Only)

| Major content | (1)<br>No test scores | (2)<br>AFQT included | (3)<br>All ASVAB included | (4)<br>% Explained by AFQT | (5)<br>% Explained by ASVAB |
|---|---|---|---|---|---|
| Mathematics | 1.857*** | 1.825*** | 1.494*** | 2.7% | 20.3% |
| | (0.186) | (0.186) | (0.211) | | |
| Humanities | -1.098** | -1.240*** | -0.825* | -12.9% | 24.9% |
| | (0.430) | (0.429) | (0.481) | | |
| Business | 3.344*** | 3.519*** | 3.685*** | -5.2% | -10.2% |
| | (0.695) | (0.695) | (0.793) | | |
| social science | -1.315** | -1.336** | -0.546 | -1.6% | 58.5% |
| | (0.608) | (0.610) | (0.697) | | |
| Education | -4.654*** | -4.413*** | -4.012*** | 5.2% | 13.8% |
| | (0.602) | (0.599) | (0.691) | | |
| Science/Engineering | 4.348*** | 3.978*** | 1.544** | 8.5% | 64.5% |
| | (0.782) | (0.777) | (0.879) | | |
| SAT Math | 21.007*** | 20.005*** | 16.779*** | 4.8% | 20.1% |
| | (1.550) | (1.523) | (1.733) | | |
| Engineering (probit) | 0.077*** | 0.071*** | 0.044*** | 6.8% | 42.3% |
| | (0.010) | (0.010) | (0.010) | | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The sample, restricted to the NLSY97, is those with at least 16 years of education who took the ASVAB tests before age 19 and who have a valid major observation. Each cell in columns 1-3 represents a different regression and reports the coefficient on "Male" from a regression of the dependent variable (given under "Major content") on gender, race/ethnicity, and the AFQT or ASVAB scores as appropriate. Column 4 is calculated by comparing the coefficients in columns 1 and 2. Column 5 is calculated by comparing columns 1 and 3.